How mobility habits influenced the spread of the COVID-19 pandemic: Results from the Italian case study

Armando Cartenì *, Luigi Di Francesco, Maria Martino

Department of Engineering, University of Campania "Luigi Vanvitelli", via Roma 29, 81031 Aversa, Caserta, Italy

HIGHLIGHTS

- We quantify the effect of mobility habits in the spread of the Coronavirus in Italy.
- Daily COVID-19 cases are directly related to the mobility habits performed 21 days before.
- Population density, PM pollutant and number of tests per day have a direct relationship with the infection.
- Temperature has an inverse relationship with the spread of the virus.
- The areas close to the outbreak had a higher risk of contagion (time-decay phenomena).

GRAPHICAL ABSTRACT
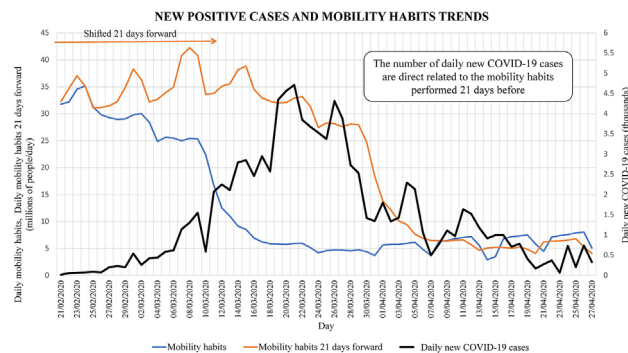
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ABSTRACT

Starting from December 2019 the world has faced an unprecedented health crisis caused by the new Coronavirus (COVID-19) due to the SARS-CoV-2 pathogen. Within this topic, the aim of the paper was to quantify the effect of mobility habits in the spread of the Coronavirus in Italy through a multiple linear regression model. Estimation results showed that mobility habits represent one of the variables that explains the number of COVID-19 infections jointly with the number of tests/day and some environmental variables (i.e. PM pollution and temperature). Nevertheless, a proximity variable to the first outbreak was also significant, meaning that the areas close to the outbreak had a higher risk of contagion, especially in the initial stage of infection (time-decay phenomena). Furthermore, the number of daily new cases was related to the trips performed three weeks before. This threshold of 21 days could be considered as a sort of *positivity detection time*, meaning that the mobility restrictions quarantine commonly set at 14 days, defined only according to incubation-based epidemiological considerations, is underestimated (possible delays between contagion and detection) as a containment policy and may not always contribute to effectively slowing down the spread of virus worldwide. This result is original and, if confirmed in other studies, will lay the groundwork for more effective containment of COVID-19 in countries that are still in the health emergency, as well as for possible future returns of the virus.

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1. Introduction

In December 2019, the city of Wuhan (Hubei, China) experienced a cluster of pneumonia cases that were monitored by the Chinese health authorities. This was caused by the new Coronavirus SARS-CoV-2 pathogen, also known as COVID-19 (e.g. Chinazzi et al., 2020). The global spread was so rapid that the World Health Organization (WHO) on 30

January 2020 officially declared that the COVID-19 epidemic was a public health emergency of international concern and later, on 12 March 2020, a global pandemic (Liu et al., 2020). In June 2020, WHO (2020) counted a total of more than 9 million confirmed cases globally and about 480 thousand deaths, reaching all countries worldwide. Countries that were initially heavily impacted by this pandemic (e.g. China and South Korea) through a massive testing regime as well as strict mobility and travel restrictions were successful in limiting the number of new locally transmitted cases (e.g. Kucharski et al., 2020).

In these few months, scientists have made advances in characterizing the novel coronavirus and have worked extensively on therapies and vaccines to combat it. Furthermore, the medico-scientific community has investigated incubation times for the virus. For example, Lauer et al. (2020) estimate that the average incubation time is 5.1 days, while in most cases (97.5%) the symptoms occur within 11.5 days of infection. The above results were used to derive the commonly applied quarantine period of 14 days (e.g. Backer et al., 2020) applied in many countries (e.g. China, the USA and major European countries like France, Germany, Italy, Spain and the UK).

With respect to the detection of positive cases, previous studies have revealed the presence of a significant fraction of asymptomatic patients infected with the virus (Bai et al., 2020; Surveillances, 2020), in addition to an unknown percentage of false positive and/or negative of each diagnostic tool among patients with COVID-19, which may have slowed down the detection time of new infections.

While the scientific community has focused in recent months mainly on health issues to defeat this virus, other key topics addressed in the literature seek to correlate the cases (deaths) of COVID-19 to both meteorological (e.g. temperature and relative humidity - Qi et al., 2020; Shi et al., 2020; Tosepu et al., 2020; Y. Wu et al., 2020; Zhu and Xie, 2020) and air quality (e.g. PM pollution - Conticini et al., 2020; Pluchino et al., 2020; X. Wu et al., 2020) variables. By contrast the incidence of human mobility on the spread of the COVID-19 was not still deeply investigated. Indeed, the lockdown of cities and regions together with specific mobility restrictions (e.g. restricted hours and/or areas, specific restrictions for citizen categories) have been common practices performed worldwide to contain and delay the spread of the COVID-19 epidemic. For example, according to Fang et al. (2020) without the Wuhan lockdown, the number of COVID-19 cases would have been 64.81% higher in the 347 Chinese cities outside Hubei province, and 52.64% higher in the 16 other cities within Hubei (Fang et al., 2020). Many countries are using expedients such as strict mobility, travel restrictions, minimum distance, and quarantine (e.g. Muller et al., 2020; Wells et al., 2020) to slow down the spread of the virus. Italy, which experienced the earliest large-scale outbreak (in Codogno, Lombardy) of COVID-19 in Europe, on 8 March enacted similar restrictions on citizens' mobility and, starting from 21 March, began to show a drop in the number of new infections.

The main European countries (such as Germany, Spain, France and lastly the UK) as well as China and the US, have implemented a 14-day quarantine period based exclusively on medical considerations related to incubation time, that is the time that elapses from initial infection to manifestation of the symptoms (or no symptoms for the asymptomatic patients). This common practice is based on the consideration that, as the incubation of infected suspects takes place within 14 days, the national health system/World Health Organization will be able to detect a new case in this time interval. By contrast, the hypothesis discussed in this research is that the time period (days) in which a new positive case of coronavirus is identified and certified, which could be called a sort of a positivity detection time, is longer than the incubation time because of possible delays between contagion and detection caused, for example, by the significant percentage of tests that prove false negative to COVID-19, or by the fraction of people who, although infected, are asymptomatic and/or initially show only mild symptoms, and therefore do not resort to health care. Furthermore, this positivity detection time, as well as the spread of COVID-19, is correlated with mobility habits, in the sense that the number of certified cases of coronavirus in one day is directly related to the number of people who made trips several days before.

To the authors' knowledge, this issue has not been investigated elsewhere, and the appropriate definition and estimation of positivity detection time and its correlation with mobility habits (e.g. daily origin-destination trips) could avoid a slowdown in detecting the infection and hence a slowdown in taking restrictive/mitigative measures.

Starting from these considerations, the aim of the paper was twofold: i) to discuss the spread of coronavirus in Italy; ii) to investigate, for the first time in the literature, the incidence of citizen mobility within the spread of the coronavirus (COVID-19) pandemic, also quantifying the positivity detection time for the Italian case study. To do this, we referred to the mobility habits of the 14–80 year-old population defined in Italy as the "active population" (source: ISTAT, 2020), that is the fraction of citizens who are individually able, unless temporary impediments, to carry out activities (e.g. work, leisure, shopping) and that therefore have autonomous mobility habits.

The proposed case study is very suitable for the purposes of this research because Italy was the first European country to experience mass contagion starting from the first outbreak. Furthermore, by May 2020 the spread had almost stopped. It is therefore possible to analyse the huge quantities of detailed contagion data (on a daily basis) and citizen mobility observed at a national scale and for a long time (before, during and after the lockdown), in addition to the effects of specific injunctions adopted by the Italian Government. To do this, quantitative estimation was also performed from the transportation perspective: the hypothesis according to which the number of certified cases of coronavirus in one day is directly related to the mobility habits made several days before, in addition to other context factors, was investigated. After all, citizen mobility could increase the probability of contagion both directly, for example via trips made by public transport where social distancing cannot be guaranteed, or indirectly (e.g. car trips) because such trips are a measure of the number of activities that a population undertakes in a certain area (trips are made for a purpose), activities that are generally based on human interactions (e.g. work, leisure, shop, sports, events, cinema), which favor the spread of the virus.

Estimates were made through a multiple linear regression model linking the number of certified daily cases (day-to-day) to socio-economic indices (e.g. number of residents; population density), environmental variables (e.g. temperature, PM pollution), health care indicators (e.g. number of swabs taken daily) and mobility habits (e.g. number people who performed trips several days before).
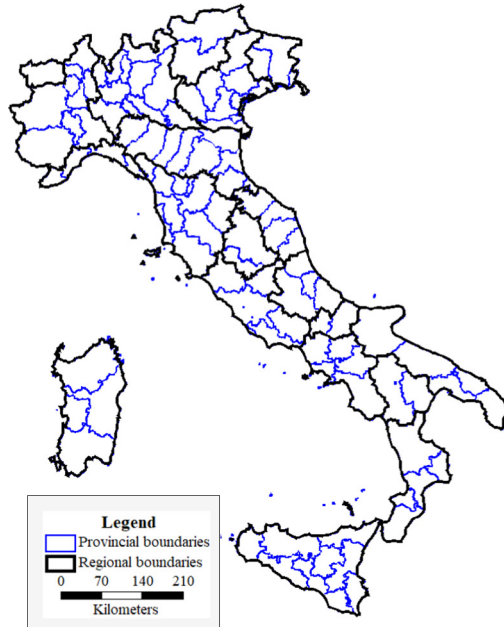
The paper is organized as follows. Section 2 reports methods and materials discussing data collection and model formulation; Section 3 describes and discusses the main results. Finally, conclusions are reported in Section 4.

2. Methods and materials

As stated above, one of the aims of the paper was to investigate the incidence of citizen mobility within the spread of the coronavirus (COVID-19) pandemic. Estimates were made through a regional (zonal) aggregation level following the classification of territorial units for statistics (NUTS) of EC (2003), although some regional-scale variables were estimates starting from a sub-zonal (provincial) analysis as described below (see the traffic zones considered in Fig. 1 on the left side). Overall, the data considered for the estimations were:

— the daily reports on COVID-19 positive cases from February 21 to May 5, 2020, source of the Italian Ministry of Health (2020);
— the Italian national census data relative to the year 2019, source of ISTAT (2020);
— the COVID-19 mobility observatory of the Italian Transport Ministry (2020), collecting about 1200 car traffic count automatic sensors data from January 2020 (pre-COVID-19) to May 2020, available at

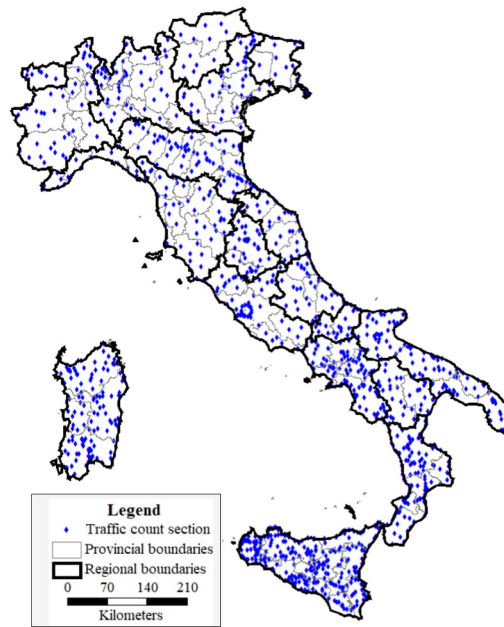## Territorial aggregation level (traffic zones)   Traffic count sections

Fig. 1. Territorial aggregation level and traffic count sections.
(Source: processing starting from EC (2003) and Italian Transport Ministry (2020).)

a national scale (see the locations in Fig. 1 on the right side) and evenly distributed throughout the Italian regions and provinces (sub-regional discretization);

— the particulate matter (PM) pollutant measures performed in 2019 by the Italian Agenzia Regionale per la Protezione Ambientale (ARPA, 2020);
— the average daily temperature measured by ilMeteo (2020) from January 2020 to May 2020;
— the Italian mobility rates estimated by Isfort (2020).

Precisely, the mobility rates considered are those estimated by the Official National Monitoring Observatory "Audimob" of Isfort (2020), which periodically carries out continuous sample surveys on the mobility of Italians through telephone and computer interviews. Through this observatory it was possible to analyse the mobility habits before and during the national lockdown in Italy. In all, 2175 interviews were conducted by Isfort (2020) between January and February (before the COVID-19 epidemic) and 1398 interviews immediately after the lockdown (8 March 2020) on a representative population sample between 14 and 80 years old. About 70% of interviews were conducted by the Computer Assisted Telephone Interview (CATI) system and about 30% by the Computer Assisted Web Interviewing (CAWI) system.

The model estimation was performed through a multiple linear regression model linking the number of certified daily cases (day-to-day) to socio-economic, environmental, health care and mobility habits variables. This tool is among those most commonly used in econometric analysis (e.g. Greene, 2012). For example, within the transport and/or economic sectors, such methods are commonly used to explain the economic development of an area driven by a transportation infrastructure considered as an input, in addition to other social, economic and territorial variables. With this type of model it is possible to separate the effects of one group of variables with respect to the others (which is the aim of the research), or, in other words, to estimate the effects of a specific variable (e.g. mobility habits), other things being equal.

The daily regional new positive cases of COVID-19 (delta new certified infections per day) provided by the Italian Ministry of Health

(2020), were considered as dependent variables, while different independent variables were tested at regional scale:

— socio-economic variables (e.g. population, population density, percentage of elderly residents over 65 years, number of employees, number of companies – relative to the year 2019);
— territorial variables (e.g. kilometers of coastline, square kilometers of mountain areas);
— environmental variables (e.g. average number of exceedances of air quality thresholds; pollutant emissions; PM average concentrations; temperature; relative humidity – relative to the year 2019 and 2020);
— health care variables (e.g. number of COVID-19 tests per day – relative to the year 2020);
— mobility habits variables (e.g. number of citizens who make at least one trip per day; transport accessibility; distance from the main Italian clusters – relative to the year 2020).

Although several model specifications and independent variables are significant the best model formulation obtained with respect to the validation tests (adj. R-squared and t-value) was:

$$y_{t,i} = \beta_1 \cdot POPdensity_t + \beta_2 \cdot PM_t + \beta_3 \cdot NTESTS_{t,i} + \beta_4 \cdot TTD_{t,i} \quad (1)$$
$$+ \beta_5 \cdot MOB_{t,i-x} + \beta_6 \cdot TEMP_{t,i-x} + Constant$$

where:

$y_{t,i}$ is the dependent variable that is number of daily new positive cases of COVID-19 detected in the t-th region on the i-th day (source: Italian Ministry of Health, 2020);

$POPdensity_t$ is the population density [10 * inhabitants/km^2] referring to the provincial capital of the t-th region (source: ISTAT, 2020);

PM_t is the particulate matter (PM) pollutant variable [number of days], measuring the number of days in 2019 in which the national PM$_{10}$ daily limit set at 50 μg/m^3 was exceeded (source: ARPA, 2020); this variable on a regional scale was obtained as a weighted (on the population) average of the corresponding variables referring to provinces within each region;

$NTESTS_{t,i}$ is the health care variable estimated by measuring the number of COVID-19 tests performed on the i-th day upon the population of the t-th region [1000 * tests/days] (source: Italian Ministry of Health, 2020);

$TTD_{t,i}$ is the weighted average travel time [hours] from the t-th region toward the initial COVID-19 cluster (outbreak) in Codogno (Lombardy) on the i-th day;

$MOB_{t,i-x}$ is the average number of 14–80 year-old people have done at least one trip (here defined as "mobility habits") "x" days before the i-th day with respect to the t-th region [100,000 * people/day]; this variable measures the circumstance investigated in this research that the number of certified cases of coronavirus in one day is directly related to the mobility habits made "x" days before;

$TEMP_{t,i-x}$ is the average daily temperature observed "x" days before the i-th day with respect to the t-th region [°C] (source: ilMeteo, 2020);

Constant variable was also estimated, accounting for all the attributes not otherwise included (explained) in the model.

As mentioned in the previous section, the first real COVID-19 outbreak in Italy was in Codogno (Lombardy). Starting from this, the epidemic spread first to neighbouring regions and then increasingly greater distances to the whole of Italy. To take into account this proximity effect, a specific variable, $TTD_{t,i}$, measuring the proximity to the outbreak of Codogno was considered in the model. To take this effect into account, we considered that this proximity variable could follow a time–decay principle. The most common non-linear functions proposed for quantifying the time–decay effect (in the literature well known as the distance–decay principle) are the inverse power and the negative exponential functions (e.g. Cheng and Bertolini, 2013; Martínez and Viegas, 2013; Hooper, 2015; Kwan, 1998). Starting from such considerations, different time–decay specifications were tested for the proposed $TTD_{t,i}$ variable, resulting that the following inverse power function was the best variable formulation for the case study in question:

$$TTD_{t,i} = \frac{TT_{t,i}}{day_i}, \quad \text{and} \quad TT_{t,i} = \frac{\sum_p CTT_{t,i,p} \cdot Pop_p}{\sum_p Pop_p} \quad (2)$$

where:

$TT_{t,i}$ is the average weighted (on the population) travel time from the t-th region toward the Codogno cluster on the i-th day;

$CTT_{t,i,p}$ is the average minimum car[1] travel time from the p-th province toward Codogno on the i-th day, estimated on the current national transport network;

Pop_p is the population of the p-th province (source: ISTAT, 2020);

day_i is the i-th day.

To the authors' knowledge, an issue which has not yet been investigated in the literature is the proper definition and estimation of positivity detection time and its correlation with mobility habits (e.g. trips/day). This time period is the average number of days in which the national health system identifies and certifies a new positive case of coronavirus, and which does not coincide (this is the hypothesis supported in this research) with the incubation time that epidemiological studies quantify as being within 14 days (with an average value of 5 days). For this purpose, through the model formulation (1), the number of new COVID-19 cases in one day was correlated with the number of people making at least one trip "x" days before, which is to say that the number of today's certified new cases are a function of the mobility habits (and hence of people's interactions) performed some days before. To do this, reference was made to the average number of 14–80 year-old people making at least one trip a day (mobility habits) estimated through the equation:

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[1] Car travel time was the transport attribute that produced the best estimates. Other transport mode travel times were also tested but not reported for brevity (e.g. bus, train).

$$MOB_{t,i} = Pop_t \cdot ADMR_t \cdot \%Var_{t,i} \quad (3)$$

where:

$MOB_{t,i}$ is the i-th day average number of 14–80 year-old people have done at least one trip in the t-th region;

Pop_t is the 14–80 year-old population (that is, as said, the socio-economic category considered in this study) living in the t-th regional area (source: ISTAT, 2020);

$ADMR_t$ is the average daily mobility rate relative to the t-th regional area before the diffusion of COVID-19 (source: Isfort, 2020); the daily mobility rate was defined as the percentage of residents in the t-th region who during a day make at least one trip, for whatever purpose, with the exception of pedestrian trips shorter than 5 min;

$\%Var_{t,i}$ is the i-th average daily percentage variation of $ADMR_t$ with respect to the pre-COVID-19 condition and relative to the t-th regional area.

On basis of the Italian Transport Ministry (2020) data, regional weighted (on the population) values of $\%Var_{t,i}$ were estimated, starting with those of the 110 Italian provinces with the following formula:

$$\%Var_{t,i} = \frac{\sum_p \%Var_{t,i,p} \cdot Pop_p}{\sum_p Pop_p}, \quad \text{and} \quad \%Var_{t,i,p} = \frac{\sum_j \%Var_{t,i,p,j} \cdot f_{p,j,i}}{\sum_j f_{p,j,i}} \quad (4)$$

where:

$\%Var_{t,i,p}$ is the i-th day average percentage variation of the p-th provincial daily mobility rate within the t-th region, with respect to the pre-COVID-19 condition;

Pop_p is the population living in the p-th province (source: ISTAT, 2020);

$\%Var_{t,i,p,j}$ is the i-th day average percentage variation of the j-th car traffic trips within the p-th province and the t-th region, with respect to the pre-COVID-19 condition (source: Italian Transport Ministry, 2020);

$f_{p,j,i}$ is the i-th day average car trips relative to the j-th traffic count section within the p-th province and the t-th region (source: Italian Transport Ministry, 2020).

The decision to estimate the trend (day by day) of the daily average percentage variation ($\%Var_{t,i}$) starting from the trend in car trips observed (car traffic counts), instead of considering, for example, the trend in public transport passengers, was made for two reasons: i) public transport (transit) trips decreased over time faster than those observed for private cars due both to the reluctance of users to use such transport services during the pandemic (which do not guarantee adequate social distancing), and to the reduction in the supply of transport services (e.g. reduction in departures/day); whereas public transport trips decreased more rapidly over time, the overall mobility rate, i.e. the average number of people making at least one trip/day (e.g. trips to buy food, pharmaceutical products or other basic necessities), followed a more gradual trend comparable with that observed for car mobility (a consideration also confirmed in terms of model estimation results as described in Section 3); ii) moreover, for this transport mode, there were much more widespread data available at a national scale, which was therefore better suited to the purposes of the research.

3. Results and discussion

As said, one of the aims of the research was to discuss the spread of coronavirus in Italy. From the data of the Italian Ministry of Health (2020) emerges that in Italy on 18 February 2020 there was the first case which in a few days led to an outbreak in Codogno near Milan in Lombardy. On 23 February 2020 the Italian Prime Minister announced the decree DL 23 February 2020, no. 6, "Control and management of

the COVID-19 epidemic", providing the implementation of measures to contain the coronavirus infection for Lombardy and Veneto, identifying r*ed zone*s where schools were closed; all public events in the regions were to be suspended. Nevertheless, the epidemic spread so rapidly that only five days after the outbreak (25 February), a total of 322 infected cases with nine deaths (3% of the total) were detected overall, with 314 (97.5%) in the North, six (1.9%) in central Italy and two (0.6%) infected cases in southern Italy (Italian Ministry of Health, 2020), most of them in the regions of Lombardy, Veneto and Emilia Romagna regions (Fig. 2).

Before the country entered lockdown on 9 March with the decree "DL no.11" (DL no. 11, 8 March 2020, "Emergency measures to contain the COVID-19 spread"), mobility habits had remained almost unchanged (Fig. 4) and many of those living or working in northern Italy had returned back to their central and southern regions of origin. Therefore, the contagion had already spread almost homogeneously in all the regions already before any mobility restriction. Fourteen days after the outbreak (10 March 2020), a total of 10,149 infected cases with 605 deaths (6% of the total) were registered nationwide, 8997 infected

(88.6%) in the North alone, 811 (8.0%) in central Italy and 341 (3.4%) in the South (Fig. 2). Despite the contagion spreading to all regions, it seems that the numbers in terms of total cases and deaths have been amplified in some regions more than in others.

Thirty-one days later (31 March 2020), a total of 10,1025 infected cases with 11,951 deaths (12% of the total) were registered all over the country, 80,690 infected (80.0%) in the North, 11,666 infected (11.4%) in central Italy and 8669 infected (8.5%) in the South (Fig. 2).

The virus continued to spread each day (Fig. 3), peaking on 21 March 2020 with a total of 53,099 cases and 4679 deaths (9% of the total). The spread of COVID-19 then gradually decreased to a safe value that allowed the start of a "*Phase* 2" (introduced by the decree DPCM of 26 April 2020), with fewer mobility limitations, on 3 May 2020, by which time 210,717 cases with 27,368 deaths (13% of the total cases) had been recorded nationwide: 168,648 infected (80%) in the North, 24,085 (11%) in central Italy and 17,984 (9%) in the South (Fig. 2).

To investigate the incidence of citizen mobility within the spread of the coronavirus (COVID-19) pandemic, the mobility habits trend was preliminary estimated applying Eq. (3). As said, through the Official
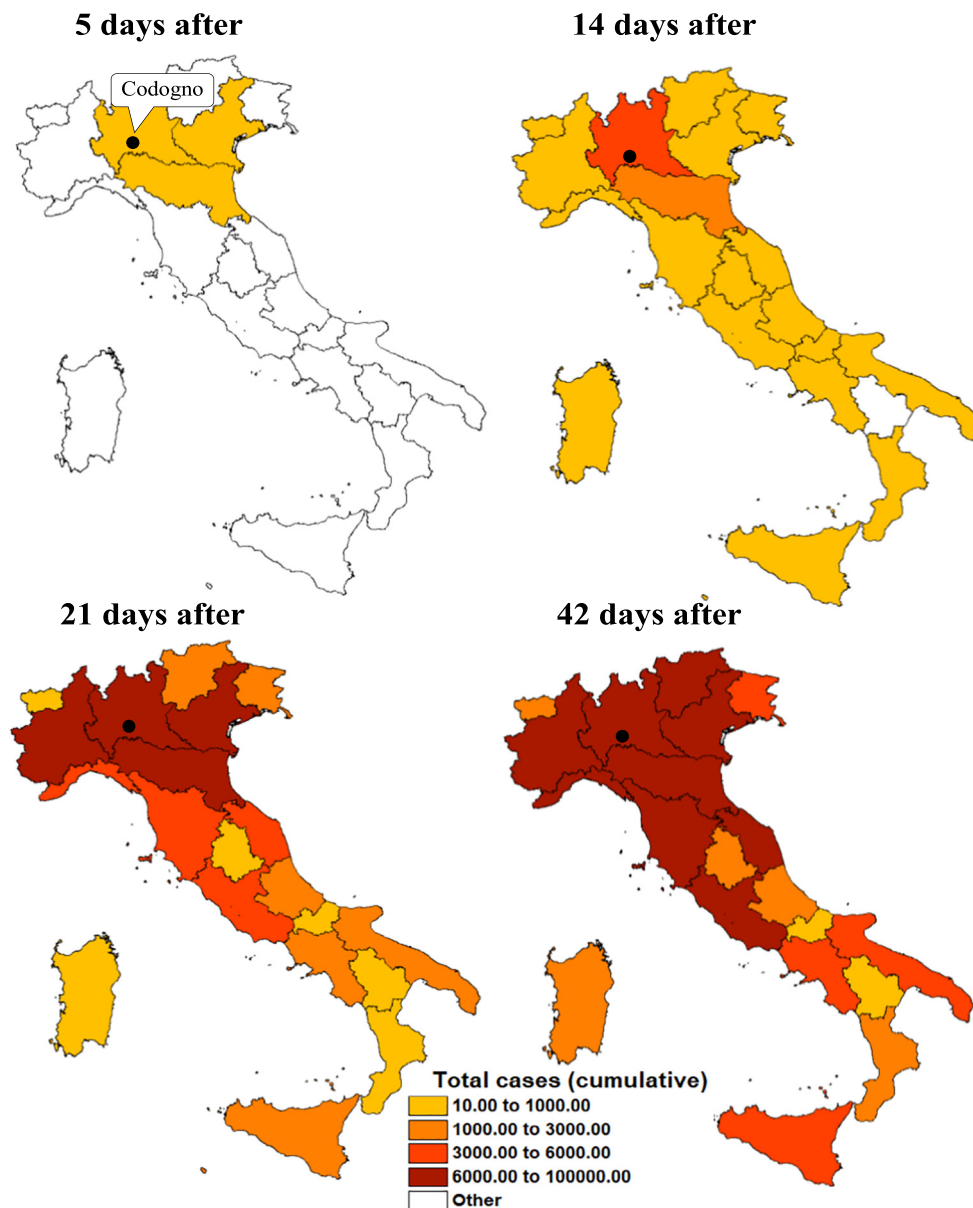

Fig. 2. The spread of COVID-19 in Italy: cumulative number of cases.
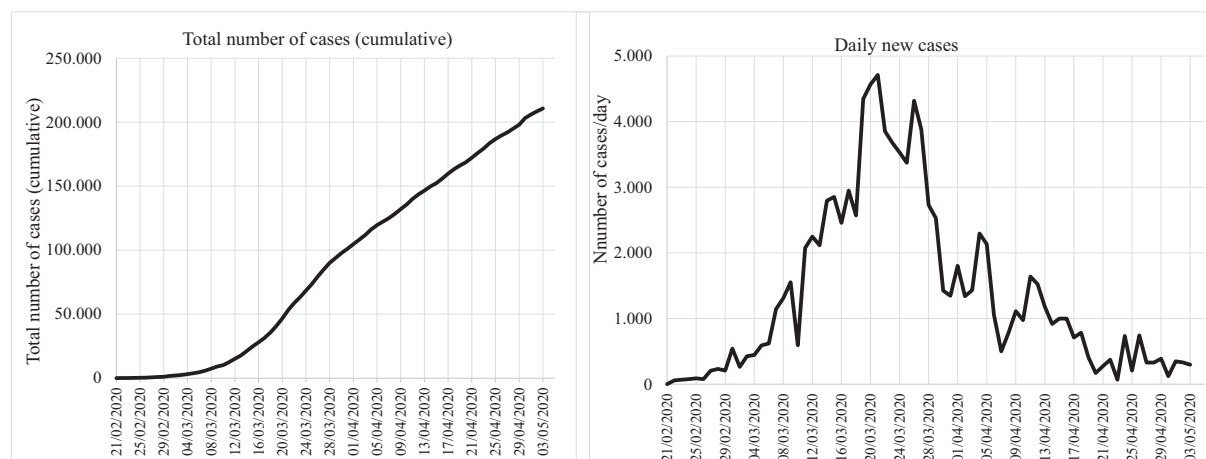(Source: processing starting from Italian Ministry of Health (2020).)

Fig. 3. The spread of COVID-19 in Italy: cumulative number of cases and daily new cases.
(Source: processing starting from Italian Ministry of Health (2020).)

National Monitoring Observatory "Audimob" of Isfort (2020), were estimated the mobility rates of the Italian "active population" (14–80 year-old population) before and during the national lockdown (as imposed by DPCM of 8 March 2020). Before the COVID-19, within the 14–80 year-old Italian population, 38 million residents (80% of the total) made at least one trip per day, while after the lockdown ordinance (DPCM, 8 March 2020) a significant reduction in mobility habits was observed and in few days a reduction to about 18 million people trips/day was observed (−42%). The estimates for the period before COVID-19 were used to evaluate the $ADMR_t$ rate, while those made in the first lockdown period (8 March 2020) were used to validate the $\%Var_{t,i}$ estimates. Results in term of daily mobility rates performed by Isfort (2020) are shown in Table 1. As a result of the lockdown, the mobility rate more than halved from 80% to 38%. In other words, 42% fewer of the population made daily trips by motorized vehicles, by bicycle or on foot (in the latter case only if exceeding 5 min). Despite the restriction regime, almost 40% of citizens on average left home every day to make at least a short trip. The decrease in the mobility rate was particularly significant in regions in central Italy (−51%), and less marked in the southern regions and the islands (−36%), while the northern regions fell just below the national average (−42%).

Table 1
Average daily mobility rate.
(Source: Isfort (2020).)

Category	Average daily mobility rate		Variation
	Pre COVID-19 lock-down	Post-ordinance "DPCM, 8 March 2020"	
Italy-wide	**80%**	**38%**	**−42%**
Geographical area			
North-west	82%	41%	−41%
North-east	77%	38%	−39%
Centre	84%	33%	−51%
South and Islands	76%	40%	−36%
Age classes			
14–29 years	80%	38%	−42%
30–45 years	86%	48%	−38%
46–64 years	83%	41%	−42%
65–80 years	61%	14%	−47%
Professional condition			
Full-employed	89%	52%	−37%
Self-employed	83%	48%	−35%
Retirees	66%	16%	−50%
Students	73%	26%	−47%
Housewives	68%	26%	−42%
Unemployed (and others)	75%	33%	−42%

As regards the age of the interviewees, starting from the restrictions the collapse in mobility was clear, especially among the over-65s where it fell by three-quarters: fewer than 15% of citizens made at least one trip by private or public transport during the lockdown. The reduction in the mobility rate was also striking among the young and very young, where the majority are schoolchildren or university students. Looking at the employment status of the interviewees, the mobility rate during the lockdown was still around 50% among workers (a little higher among employees than the self-employed), who recorded a 35% decrease in trips, just 5–7 points below the general[2] average. On the other hand, the trips of retirees were almost eliminated: their mobility rate fell from 66% pre-COVID-19 to 16% under lockdown. There was also a very marked reduction in student mobility (from 73% to 26%), which was of course massively affected by school closures (DPCM of 9 March 2020).

For each of the 20 Italian regions, the 14–80 year-old population mobility habits and its day by day evolution before, during and after (beginning of business recovery "Phase 2") the COVID-19 pandemic in Italy was therefore estimated through Eq. (3) (results in Fig. 4). The estimates in their aggregate form (at the national scale) were also compared with those available in some official open-source databases specific to the Italian case study, including the COVID-19 mobility trends of Apple Inc. (driving data, 2020), the COVID-19 Community Mobility Reports of Google LLC (transit stations percent change from baseline data, 2020), the Mobility DataLab of Octotelematics and Infoblu S.p.A. (car trip, 2020) specific to road traffic in Italy and the survey results performed by Isfort (2020) discussed above and reported in Table 1. The results of the comparison (Fig. 4) show that the estimated mobility habits trend is consistent with those of the available databases, in addition to those of the Isfort (2020) investigation.

As stated above, the main aim of the paper was to investigate the incidence of mobility habits within the spread of the Coronavirus (COVID-19) pandemic, also quantifying the average *positivity detection time* for the Italian case study. Estimates were made through the multiple linear regression model in Eq. (1), linking the number of certified daily cases (day-to-day) to socio-economic, environmental, health care and mobility zone-specific variables at regional scale. The length of time considered spans the period from the first new cases observed on 21 February 2020 resulting from the outbreak in Codogno near Milan in Lombardy, to 20 April 2020 (60 consecutive days) when the daily infection curve reached its lowest point (Fig. 3). Furthermore, other time

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[2] It should be pointed out that the mobility rate of employees, as well as all the others analysed, is to be determined with reference to all trips with different purposes, not only for work.
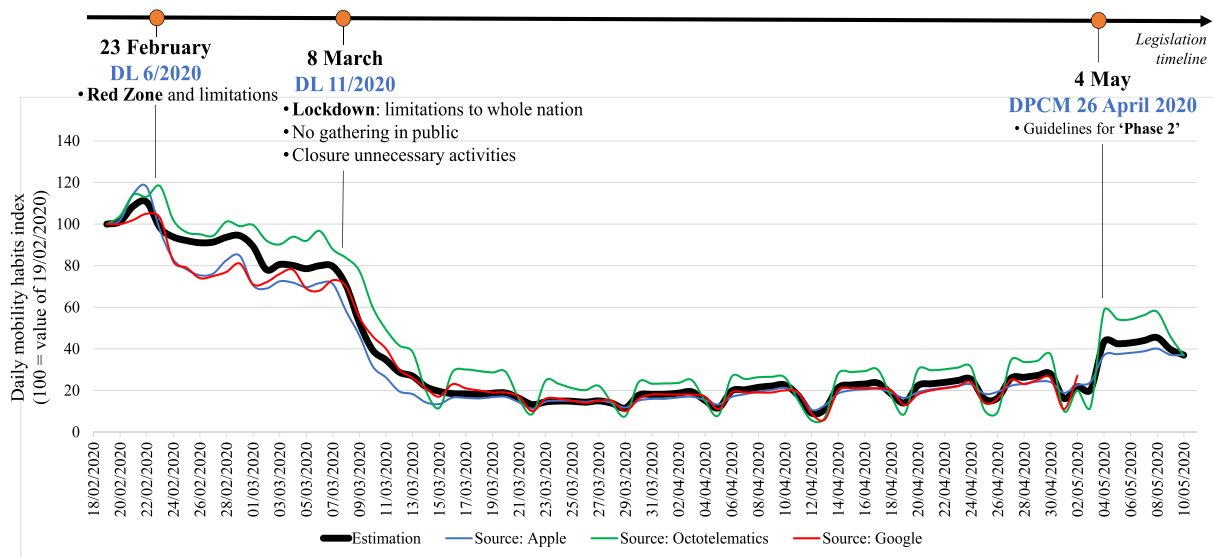
Fig. 4. Legislation timeline and estimated trend in daily mobility habits index in Italy.

periods were also tested and not reported for brevity so as not to produce significant differences in estimation results.

Although several model specifications and independent variables are significant, in Table 2 the results of only the best model formulation with respect to the validation tests (adj. R-squared and t-value) are reported. All the parameters are statistically significant (>95% significance) and with the expected sign. The R-squared (adj. R-squared) is equal to 0.427 (0.424). R-squared values below 0.5 are not an unusual result, as observed in similar case study applications (e.g. Herranz-Loncán, 2007; González and Nogués, 2019).

With respect to socio-economic variables, Italy is characterized by uneven population density within the area of the country and for this reason, although the average regional population density, the model that gave the best results includes a population density variable ($POPdensity_t$) referring to the provincial capital of the region, that is the area where most of the population live. In the Italian regions, the average population density is about 183 inhabitants/km^2, while the corresponding provincial capital population density is about 540 inhabitants/km^2 (+66%). The territorial area where this difference is more evident is the Campania region where the province of Naples (the highest population density area of the country) with 2617 inhabitants/km^2 is 84% denser than its region average value (424 inhabitants/km^2). This circumstance means that areas with higher population densities have a higher probability of contagion, being (on average) less able to guarantee social distancing (increase in social activities with overcrowding). Moreover, more than 19 million inhabitants live in these provincial capitals of the region.

Number of regional tests per day ($NTESTS_{t,i}$) is the health care variable estimated by measuring the number of COVID-19 tests performed every day upon the population of the region. This variable, which represents the second variable in "weight" with respect to the standardized coefficients estimated (Table 2), explains the circumstance that, all else being equal, the more tests are conducted, the greater is the probability of finding positive cases (especially with respect to the asymptomatic population).

As mentioned, the first real COVID-19 outbreak in Italy was in Codogno (Lombardy). Starting from this, the epidemic spread first to neighbouring regions and then increasingly greater distances to the whole of Italy. To take into account that the areas close to Codogno have greater daily exchange trips with the outbreak area, and therefore a greater probability of contagion, a specific variable ($TTD_{t,i}$) measuring the proximity to the outbreak of Codogno was considered in the model. Moreover, with the passing of the days this proximity effect from the

initial outbreak (trips from Codogno and Lombardy) decreased, resulting in new contagion produced by the local mobility of residents in the region. To take this effect into account, we considered that this proximity variable could follow the time–decay principle described by Eq. (2). Through this variable formulation the proximity effect was greatest within the first days and then "decayed" in its incidence with the passing of the time.

Mobility habits were the variable ($MOB_{t,i-x}$) that best explained the number of COVID-19 infections (in term of "weight" with respect to the standardized coefficients estimated and reported in Table 2). This variable measures the circumstance investigated in this research that the number of certified cases of coronavirus in one day is directly related to the mobility habits made "x" days before. To estimate the most representative number of "days before" that influence the new cases in a day, many thresholds were tested in terms of model validation tests, obtaining that trips 21 days before was the best variable to reproduce the data observed. This result is also qualitatively observable from Fig. 5 through which it may be seen that the daily mobility habits shifted 21 days ahead (left axis of Fig. 5) closely reproduce the observed trend of new daily cases of COVID-19 (right axis of Fig. 5).

Furthermore, among the environmental measures, a particulate matter pollutant variable (PM_t) was significant, measuring the number of days in 2019 in which the national PM$_{10}$ daily limit set at 50 μg/m^3 was exceeded. This measure on a regional scale was obtained as a weighted (on the population) average of the corresponding variables referring to provinces within each region, meaning that areas with higher population and with lower air quality have a higher probability of contagion. Overall, the data analysis shows how the areas of the country with the highest PM pollution are those of northern Italy (e.g. province of Milan in Lombardy and Turin in Piemonte), where are mainly located the industrial areas and/or most of the population live, according to with the circumstance that PMs are mainly generated by industries, heating (e.g. home, office) and transport sector (e.g. mobility habits). The opposite occurs for areas in the south, characterized by an economy mainly based on tourism and agriculture. This variable explains, as observed in other case studies, the (positive) correlation between the number of cases per day and the average pollution in the area. With respect to air quality impacts upon the spread of COVID-19, some recent research has shown that people living with long-term exposure to air pollution are more likely to become infected by Coronavirus. For example, Conticini et al. (2020) conclude that a prolonged exposure to air pollution may partly explain a higher presence of viral agents such as SARS-CoV-2.

Table 2
Model estimation results.

Variable		Coefficient (βi)	Std. error	t-Value	P-value	Standardized coefficient
POPdensity_t	Population density [10 ∗ inhabitants/km²]	0.159	0.069	2.299	0.022	0.057
PM_t	Particulate matter pollutant [number of days]	0.858	0.291	2.944	0.003	0.090
NTESTS_{t,i}	Number of tests per day [1000 tests/days]	1.904	0.254	7.495	<0.0001	0.201
TTD_{t,i}	Travel time decay from the outbreak [h]	−4.949	2.119	−2.336	0.020	−0.052
MOB_{t,i−x}	Mobility habits 21 days before [100,000 ∗ people/day]	9.809	0.531	18.460	<0.0001	0.511
TEMP_{t,i−x}	Temperature [°C]	−6.557	1.388	−4.724	<0.0001	−0.107
Constant [number]		18.340	9.270	1.979	0.048	<0.0001
Number of observations						1200
R-squared						0.427
Adj. R-squared						0.424
F-statistic (6, 1193)						148.359
P-value(F)						1.30E−140

At the same time, Pluchino et al. (2020) identified the PM_{10} concentration as a factor of the vulnerability component of the risk in COVID-19 analysis. Indeed, in a study conducted by X. Wu et al. (2020) it was shown that an increase of 1 μg/m³ in $PM_{2.5}$ involves an 8% increase in the COVID-19 death rate. From another research perspective, few studies have linked air pollutants with one of the causes that make COVID-19 spread so rapidly (e.g. Coccia, 2020; Piazzalunga-Expert, 2020; Setti et al., 2020).

Finally, temperature ($TEMP_{t,i−x}$) was also significant and represents the third variable in "weight" with respect to the standardized coefficients estimated (Table 2). This variable is negatively correlated with the COVID-19 new cases, meaning that the warmer areas of the country (i.e. south regions and island) have probably contributed to contain the virus contagion. This result is coherent with observed in other case studies, where several researches have observed that temperature and relative humidity positively influence the spread of COVID-19 (e.g. Qi et al., 2020; Shi et al., 2020; Tosepu et al., 2020; Y. Wu et al., 2020; X. Wu et al., 2020; Zhu and Xie, 2020). For example, in Hubei (China) Qi et al. (2020) observed that every 1 °C increase in the average temperature with relative humidity in the range from 67% to 85% led to a 36% to 57% reduction in confirmed COVID-19 cases. In addition, the authors also concluded that every 1% increase in relative humidity led to an 11% to 22% reduction in daily confirmed cases with average temperatures in the range from 5.0 °C to 8.2 °C.

4. Conclusions

The research discussed in this paper concerns the topics of both the "atmosphere" (air quality and temperature impacts) and the "anthroposphere", in the sense of the Earth's research area dealing with the part of the environment that is made or modified to satisfy human activities and habits, where transportation system and the corresponding people mobility trips cover a central role. Precisely, the aim of the paper was to investigate the incidence of citizens' mobility habits within the spread of the Coronavirus (COVID-19) pandemic for the Italian case study. The conjecture that the number of new certified cases of coronavirus in one day is directly related to the number of trips made several days before, in addition to environmental and other context factors, was investigated. Another issue discussed in this paper and unexplored in the literature is the appropriate definition and estimation of the *positivity detection time* and its correlation with mobility habits. The thesis was that this time period generally exceeds the *incubation time* due to many external factors such as *false negative* test results to COVID-19 or people who, albeit infected, are asymptomatic and/or initially show only mild symptoms, and therefore do not resort to health care.

To pursue the research aims, quantitative estimation was made through a multiple linear regression model. Estimation results showed that mobility habits represent the variable that mainly explains (from
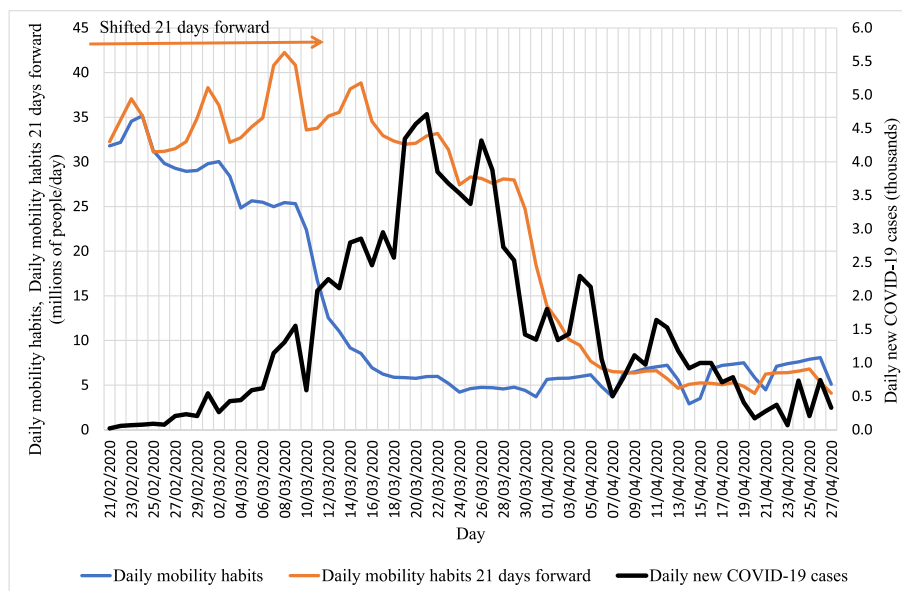

Fig. 5. Delta new COVID-19 cases/day, observed daily 14–80 year-old population mobility habits and daily mobility habits shifted 21 days forward (positivity detection time).

a statistical perspective) the number of COVID-19 infections. Nevertheless, significant in explain the spread of the COVID-19 were also the environmental variables (temperature and PM pollutant), underling how environmental issues cover a central role in multidisciplinary researches (e.g. healthcare and transport sectors). Furthermore, other variables were significant in reproducing the spread of the coronavirus in Italy, among which the number of tests per day and the proximity to the first Italian outbreak, especially in the initial stage of infection (following a time-decay phenomenon).

Furthermore, research results showed that the number of new COVID-19 cases in one day is directly related to the trips performed three weeks before for the Italian case study. This threshold of 21 days could be considered a sort of *positivity detection time* measure, meaning that quarantine of mobility restrictions (e.g. lockdown; restrictive/mitigative actions; social distance) commonly set in 14 days, and based only on incubation-based epidemiological considerations, is underestimated as a containment policy and may have produced a possible (dangerous) slowdown in the certification of the infections and therefore the slowdown in implementing restrictive/mitigative action, resulting in more Coronavirus contagion and deaths worldwide.

This result is original and, if confirmed in other case studies, would lay the groundwork for more effective containment of COVID-19 in countries that are still experiencing a health emergency, as well as for possible future returns of the virus, or for other pandemics.

CRediT authorship contribution statement

Armando Cartenì: Conceptualization, Methodology, Supervision, Data curation, Formal analysis, Validation, Writing - original draft, Writing - review & editing. **Luigi Di Francesco:** Formal analysis, Writing - original draft, Writing - review & editing. **Maria Martino:** Data curation, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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